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Enhancing Arrhythmia Classification Performance using Hybrid CNN and SVM

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Abstract

Cardiac arrhythmia, a disorder in the heart's rhythm, can lead to serious complications. This study presents a hybrid cardiac arrhythmia classification model that integrates a one-dimensional Convolutional Neural Network (1D-CNN) with a Support Vector Machine (SVM) classifier to improve the recognition of ECG heartbeat patterns. The model was evaluated using the MIT-BIH Arrhythmia dataset available on Kaggle. Experimental results show that the hybrid 1D-CNN-SVM architecture achieves 96.84% accuracy, outperforming the baseline 1D-CNN with SoftMax, which attained 83.64% accuracy. The hybrid approach also demonstrates substantial improvements in class-balanced metrics, with Macro Precision increasing from 0.58 to 0.81 and Macro F1-Score rising from 0.63 to 0.85. These results indicate that the proposed architecture not only enhances overall predictive performance but also delivers more stable and reliable classification across all arrhythmia categories, particularly minority classes prone to misclassification. By effectively reducing false positives and maintaining a stronger precision–recall equilibrium, the model offers improved clinical relevance for automated ECG analysis. Future research may further optimize CNN–SVM hyperparameters, validate generalization across diverse ECG datasets, and explore deployment on low-power wearable monitoring systems.

Keywords:
Arrhythmia, ECG, Classification, 1D-CNN, SVM

1. Introduction

Cardiovascular diseases remain the leading cause of global mortality, and arrhythmias constitute one of the most critical abnormalities due to their potential to trigger stroke, cardiac arrest, and sudden death. Health organizations consistently emphasize that early detection is essential to reducing fatal outcomes. However, arrhythmia often presents subtle or irregular electrical patterns that challenge manual interpretation, particularly in large-scale clinical environments where rapid assessment is required. These issues motivate the development of automated classification systems that process ECG data efficiently and improve diagnostic reliability [1], [2].

Electrocardiogram (ECG) signals serve as the primary modality for arrhythmia diagnosis because they capture the heart's electrical activities with high temporal resolution. Clinicians rely on ECG waveforms to identify abnormalities, yet visual inspection remains prone to subjective errors, inter-observer variability, and fatigue. Irregular beat morphology, noise disturbances, and variability among patients further complicate traditional assessment. These limitations highlight the need for computational approaches that automatically extract robust features and classify arrhythmia patterns accurately using standardized signal datasets [3].

Recent studies in medical computing show that hybrid and deep learning models significantly enhance diagnostic performance across various health applications. Fusion

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models and hybrid architectures demonstrate their ability to capture complex nonlinear patterns, improve prediction stability, and outperform conventional machine learning methods. These findings reinforce the potential of combining complementary model strengths to handle high-dimensional biomedical signals, suggesting a promising direction for arrhythmia classification tasks that require precise temporal and morphological analysis [4], [5], [6].

CNNs emerge as a leading approach for one-dimensional signal processing due to their capability to learn hierarchical features, reduce dependency on handcrafted descriptors, and generalize across diverse data variations. Studies show that 1D-CNNs excel in extracting discriminative temporal features from ECG sequences and performing efficient end-to-end classification. CNN-based methods also demonstrate strong performance in anomaly detection, heritage pattern recognition, vibration monitoring, and multiple biomedical applications, proving their flexibility and high modeling capacity [7], [8], [9], [12].

SVMs remain widely used in medical classification due to their strong margin maximization principle, stability in small or imbalanced datasets, and consistent performance in high-dimensional feature spaces. SVMs show strong discriminative capabilities for decision boundaries, making them suitable for ECG-based arrhythmia classification. Their mathematical formulation provides reliability and interpretability, and previous applications demonstrate their effectiveness in spam detection, biomedical signal classification, and fault detection in clinical systems [10], [11].

The integration of CNN and SVM emerges as an important direction because CNNs effectively extract deep temporal–spatial features while SVMs provide powerful decision boundaries for final classification. Prior research confirms that hybrid CNN–SVM models outperform standalone CNN or SVM architectures in multiple biomedical tasks, including arrhythmia detection, ECG auto-encoder–SVM classification, and spectrogram-based ECG analysis. These results indicate that hybridization enhances feature discrimination and improves model generalization, especially in scenarios with noisy or highly variable heartbeat patterns [17], [18], [19].

The availability of high-quality ECG benchmark databases strengthens the feasibility of developing robust hybrid models. The MIT-BIH Arrhythmia Database remains the most widely used dataset for algorithm benchmarking due to its well-annotated recordings and extensive representation of arrhythmia classes. Researchers consistently adopt this dataset for training and evaluation, enabling reproducibility and standardized comparison across studies. Additional works demonstrate that deep feature extraction, transfer learning, attention mechanisms, and recurrent units achieve improved performance when applied to these ECG signals, establishing a strong foundation for new hybrid architectures [16], [21], [24], [25].

Model performance evaluation follows standardized international guidelines to ensure reliability in clinical contexts. Studies report results according to recommended metrics such as accuracy, sensitivity, specificity, and confusion matrices, aligning with the ANSI/AAMI EC57 standard for rhythm classification. Despite advancements, challenges remain in capturing subtle arrhythmia variations, managing inter-patient differences, and handling noisy signals. These limitations motivate further exploration of hybrid CNN–SVM architectures to achieve more accurate and stable arrhythmia classification that supports real-world diagnostic environments [13], [20], [22], [23], [26].

2. Related Works

Early research on cardiovascular disease detection highlights the global importance of automated analysis systems, especially for cardiac rhythm abnormalities. Studies emphasize that traditional ECG interpretation suffers from inconsistencies due to noise, morphological variations, and human error, motivating the development of machine learning-based arrhythmia classifiers. Foundational works on ECG acquisition and annotation demonstrate how clinical markers such as P-wave irregularities, QRS width, and ST-segment deviation support automated diagnosis, yet these approaches rely heavily on handcrafted features that limit generalization across patient populations [1], [2], [3].

Recent developments show that deep learning models significantly enhance ECG analysis by learning hierarchical features directly from waveform data. 1D-CNNs emerge as dominant models due to their ability to capture temporal and morphological patterns efficiently. Surveys and empirical studies confirm the superiority of CNNs over traditional feature-engineering approaches, especially when dealing with complex, nonlinear physiological signals. However, these models still face challenges related to overfitting, class imbalance, and sensitivity to noise, limiting their robustness when applied to diverse real-world ECG signals [7], [9], [12].

Hybrid deep learning models have gained attention for improving diagnostic accuracy in clinical tasks beyond cardiology. Works in pneumonia prediction, glucose forecasting, and neuroimaging classification demonstrate that combining multiple architectures—such as CNN with wavelet transforms, LSTM encoders, or residual blocks—yields better predictive stability and generalization. These studies show that hybrid systems benefit from complementary feature extraction mechanisms, yet their computational cost increases significantly, and their performance depends heavily on high-quality training data and parameter tuning [4], [5], [6].

Research on ECG-based arrhythmia detection shows extensive use of CNNs, LSTMs, GRUs, and attention mechanisms to improve heartbeat classification performance. Recent models incorporate attention layers to focus on salient ECG segments, achieving improved interpretability and accuracy. Despite these advances, many of these architectures require large datasets and long training times, and they often lack interpretability at the decision boundary level. Furthermore, recurrent units such as GRU or LSTM may introduce temporal redundancy that slows computation in real-time applications [21], [22], [23].

A number of studies propose hybrid models specifically tailored for arrhythmia classification. One influential work combines CNN with GRU and multiclass SVM to enhance classification stability, reporting strong performance across multiple arrhythmia classes. Other researchers integrate CNN-based feature extractors with SVM classifiers to leverage CNN's representation learning and SVM's margin-based discrimination. These hybrid models consistently outperform single-architecture systems, but many studies do not explore kernel optimization deeply, and several lack extensive cross-dataset validation, which limits their real-world applicability [17], [19], [20].

Classical machine learning approaches also contribute to arrhythmia research. Works employing SVM classifiers, auto-encoders with SVM output layers, and RBF-kernel SVMs demonstrate strong performance on well-structured ECG datasets. These models remain popular for their robustness in small-sample scenarios and their strong generalization properties. However, their reliance on hand-crafted features or shallow feature extraction remains a limitation, as they often fail to capture subtle waveform characteristics that deep models can detect. Thus, they perform well under ideal conditions but drop in accuracy when applied to noisy or heterogeneous ECG data [10], [11], [18].

The MIT-BIH Arrhythmia Database has played a critical role in advancing algorithm development for cardiac rhythm classification. Its standardized annotations and wide range of arrhythmia types make it the most commonly used benchmark for ECG-based studies. Research utilizing this dataset introduces techniques such as transfer learning, beat segmentation, and deep representation learning to improve classification accuracy. Nevertheless, many studies report performance degradation when models trained on MIT-BIH are tested on external datasets, indicating that domain shift and inter-patient variability remain persistent research challenges [16], [24], [25].

Lastly, recent evaluations of cardiac rhythm algorithms follow standardized reporting guidelines such as the ANSI/AAMI EC57 protocol, which ensures comparability among studies. Despite improvements in deep learning and hybrid models, limitations continue to appear in model interpretability, computational demands, electromagnetic noise sensitivity, and the difficulty of distinguishing morphologically similar arrhythmias. These limitations motivate ongoing research into hybrid CNN–SVM methods, which aim to combine deep temporal–spatial feature extraction with strong discriminative decision boundaries to enhance both accuracy and robustness in arrhythmia classification [13], [26].

3. Proposed Method

This research proposes a hybrid approach for cardiac arrhythmia classification by combining a 1D-CNN for automatic feature extraction and an SVM for final classification. A 1D-CNN is a variant of the CNN designed specifically to analyze sequential or time-series data, such as ECG signals [7]. The 1D-CNN was specifically chosen as the feature extractor because of its inherent ability to learn hierarchical patterns and temporal dependencies directly from raw 1D signal data. This avoids the need for complex, domain-specific manual feature engineering, making the process more automated and robust. The architecture automatically extracts relevant features through its main layers [9]. The convolution layer applies a series of learnable filters (kernels) to detect local patterns in the input signal.

The core 1D convolution operation for an input signal x and a filter w is defined as:

$$y[n] = (x * w)[n] = \sum_{k=0}^{K-1} x[n-k] \cdot w[k] \tag{1}$$

A non-linear activation function, such as ReLU $f(x) = \max(0, x)$, is then applied to the output. Following convolution, a pooling layer (typically max pooling) is used to reduce the spatial dimensions of the feature maps, thereby decreasing computational load and making the feature representation more robust [23].

As a final classification layer, we utilize SVM to find an optimal hyperplane that separates data into different classes with the largest possible margin [10]. The SVM was chosen to replace the standard SoftMax classifier due to its distinct advantages. Softmax calculates probabilities that can be sensitive to the class imbalance and overlapping features often found in ECG data. The SVM's principle of margin maximization creates a more robust decision boundary. This approach often leads to better generalization, especially when classifying the high-dimensional feature vectors generated by the preceding CNN.

In this hybrid approach, the SVM acts as the final classifier, taking the feature vectors extracted by the 1D-CNN as its input. SVM achieves this by solving the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \xi_i \tag{2}$$

Subject to $y_i.(w \cdot \phi(x_i) + b) \geq 1 - \xi_{,} and \xi_i \geq$ where C is the regularization parameter. For non-linear problems, SVM uses the "kernel trick"; this study uses the Radial Basis Function (RBF) kernel, defined as:

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \tag{3}$$

In this hybrid approach, the SVM acts as the final classifier, taking the feature vectors extracted by the 1D-CNN as its input.

4. Experimental Setup

1. Dataset

This study utilizes the "ECG Heartbeat Categorization Dataset" publicly available on Kaggle. This dataset is derived from the MIT-BIH Arrhythmia Database [24] and was processed by Kachuee et al. [25]. The heartbeats are classified into five main categories according to the AAMI EC57 standard [26]: Normal (N), Supraventricular (S), Ventricular (V), Fusion (F), and Unclassifiable (Q). The detailed annotations for each category are presented in **Table 1** describes the dataset consisting of 87,554 samples as training and 21,892 samples as a testing dataset, where each sample is represented by 187 signal points.

Table 1. AAMI EC57 Standard Categories and Annotations

Category	Annotations
N	Normal, Left/Right bundle branch block, Atrial escape, Nodal escape
S	Supra-ventricular premature, Atrial premature, Aberrant atrial premature, Nodal premature
V	Premature ventricular contraction, Ventricular escape
F	Fusion of ventricular and normal
Q	Paced, Fusion of paced and normal, Unclassifiable

2. Preprocessing

The raw CSV data underwent a structured preparation process before model training. The dataset was first divided into training (80%) and validation (20%) subsets using a stratified split to preserve class distribution. The feature values were then standardized with a scaler fitted exclusively on the training portion to avoid leakage. To mitigate the severe class imbalance, class weights were computed in balanced mode and incorporated into the loss function. Finally, the data was reshaped into a three-dimensional format of (samples, 187, 1) to align with the input requirements of the 1D-CNN architecture.

3. Hybrid Model Architecture

The proposed system employs a two-stage hybrid architecture, as visualized in Fig. 1.

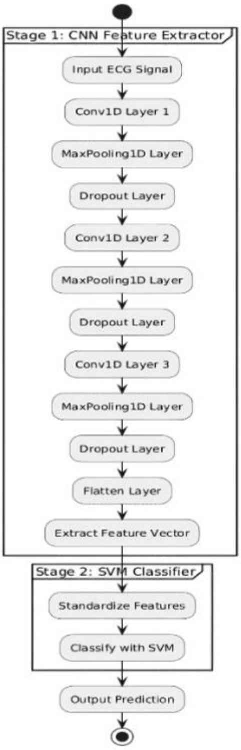

Fig. 1. Architecture of the Proposed Hybrid 1D-CNN-SVM Model

In the first stage of model construction, we conduct a feature extractor using a 1D-CNN to automatically extract discriminative features from the raw ECG signals. The architecture is detailed in Table 2. All Conv1D layers use padding='same'.

Table 2. Architecture of the 1D-CNN Feature Extractor

Layer	Type	Parameters
1	Input Layer	Accepts input of shape (187, 1)
2	Conv1D Layer 1	32 filters, kernel size 5, ReLU activation
3	MaxPooling1D Layer 1	Pool size 2
4	Dropout Layer 1	Rate 0.5 to prevent overfitting
5	Conv1D Layer 2	64 filters, kernel size 3, ReLU activation
6	MaxPooling1D Layer 2	Pool size 2
7	Dropout Layer 2	Rate 0.5
8	Conv1D Layer 3	128 filters, kernel size 3, ReLU activation
9	MaxPooling1D Layer 3	Pool size 2
10	Dropout Layer 3	Rate 0.5
11	Flatten Layer	Converts to a 1D feature vector of size 2944

At the second stage, we employ SVM for the final classification to obtain the final classification result. The feature vectors extracted by the 1D-CNN are first standardized using a new StandardScaler instance and then fed into the SVM. In this study, we apply an SVC from Scikit-learn with a Radial Basis Function (RBF) kernel, C=1.0, and gamma='scale'.

4. Evaluation Metrics

The performance of the models was evaluated using a confusion matrix, which provides the counts of true positives, false positives, true negatives, and false negatives for each class, forming the basis for computing key classification metrics. From this matrix, precision was derived to measure the proportion of correctly predicted positive instances relative to all predicted positives, while recall quantified the model's ability to identify actual positive cases. The F1-score, calculated as the harmonic mean of precision and recall, offered a balanced assessment of performance under class imbalance. Additionally, the support value indicated the number of true instances for each class in the dataset, providing necessary context for interpreting the reliability and stability of the evaluation metrics.

5. Result and Analysis

At the first stage, we train the model using a pure CNN component as a complete classification model with a Softmax to learn the feature representations. The training process was monitored using a validation set. To prevent overfitting, we adopt the Early Stopping callback to halt training when the validation loss stops improving. This approach ensures that the feature extractor is trained to its optimal point for generalization.

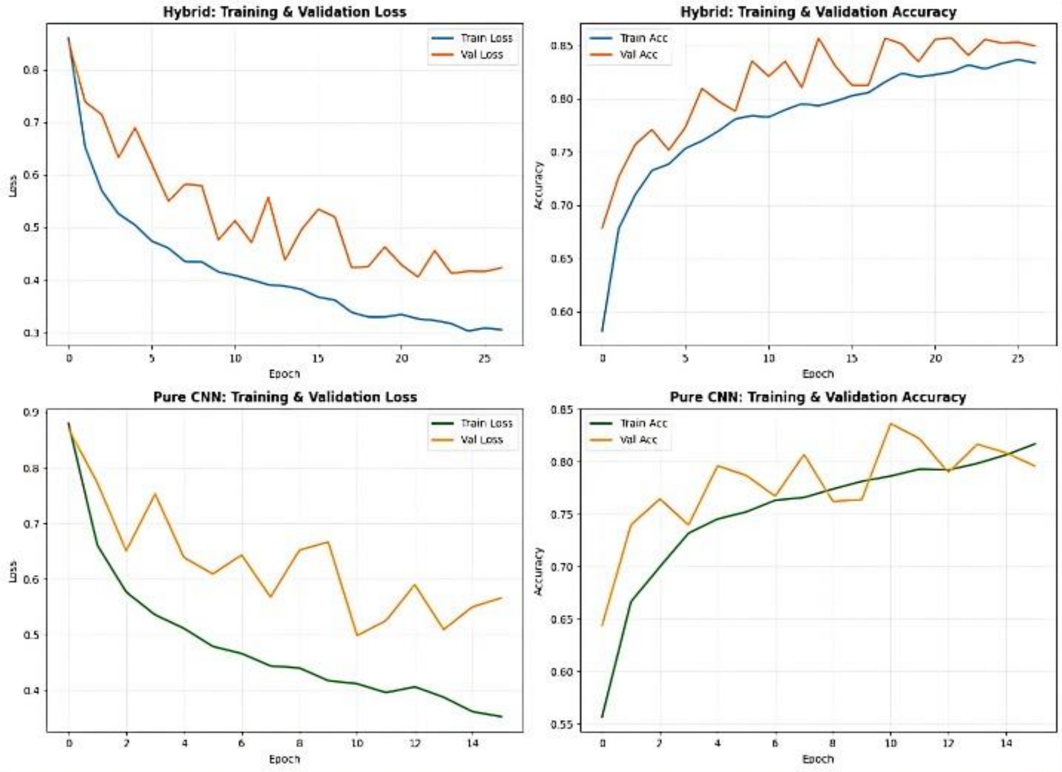

Fig. 2. Training and Validation Curves for the CNN Models

The learning curves in Fig. 2 show the training process for both models. The feature extractor component for the hybrid model (top plots) shows stable convergence, reaching a peak validation accuracy of approximately 85.7%. Similarly, the pure CNN model (bottom plots) trained to a peak validation accuracy of around 83.7%, although its validation loss curve shows more fluctuation. The pure 1D-CNN model (with a softmax classifier) was evaluated on the independent test set. The model achieved an overall accuracy of 83.64%. The detailed classification report is shown in Table 3.

Table 3. Classification Report of the Pure 1D-CNN Model

Class	Precision	Recall	F1-Score	Support
N	0.9907	0.8184	0.8963	18118
S	0.2646	0.7824	0.3955	556
V	0.6443	0.9206	0.7580	1448
F	0.1041	0.9136	0.1869	162
Q	0.8755	0.9751	0.9226	1608
Accuracy			0.8364	21892
Macro Avg	0.5758	0.8820	0.6319	21892
Weighted Avg	0.9343	0.8364	0.8711	21892

The next stage is using a hybrid model, 1D-CNN and SVM to train the model classifier. In this process, it utilized 1D-CNN for extracting features and employed the SVM classifier as the final classifier on the same independent dataset. The hybrid model achieved an overall accuracy of 96.84%. The detailed classification report is presented in Table 4.

Table 4. Classification Report of the Hybrid 1D-CNN-SVM Model

Class	Precision	Recall	F1-Score	Support
N	0.9885	0.9763	0.9823	18118
S	0.6338	0.7968	0.7060	556
V	0.9451	0.9282	0.9366	1448
F	0.5091	0.8642	0.6407	162
Q	0.9894	0.9857	0.9875	1608
Accuracy			0.9684	21892
Macro Avg	0.8132	0.9102	0.8506	21892
Weighted Avg	0.9731	0.9684	0.9701	21892

According to the experimental result, the hybrid 1D-CNN-SVM model achieved an accuracy of 96.84%, which is 13.2% higher than the 83.64% accuracy achieved by the standard 1D-CNN model with a SoftMax classifier. This superiority is not just evident with accuracy but also in the confusion matrices (Fig. 3 and Fig. 4). The pure CNN model (Fig. 4) exhibits significant confusion, particularly in misclassifying the majority 'Normal' (N) class. It incorrectly labeled over 3,000 'N' instances as other arrhythmia types (1,194 as 'S', 699 as 'V', and 1,187 as 'F'). This indicates that the features extracted by the CNN are highly overlapping, and the SoftMax layer fails to establish a clear boundary.

In contrast, the hybrid model (Fig. 3) drastically rectifies this weakness. It correctly identifies 'N' beats far more accurately, with misclassifications into 'S' and 'F' dropping by 79% and 90% respectively. This ability to create a cleaner separation is the key to the hybrid model's success.

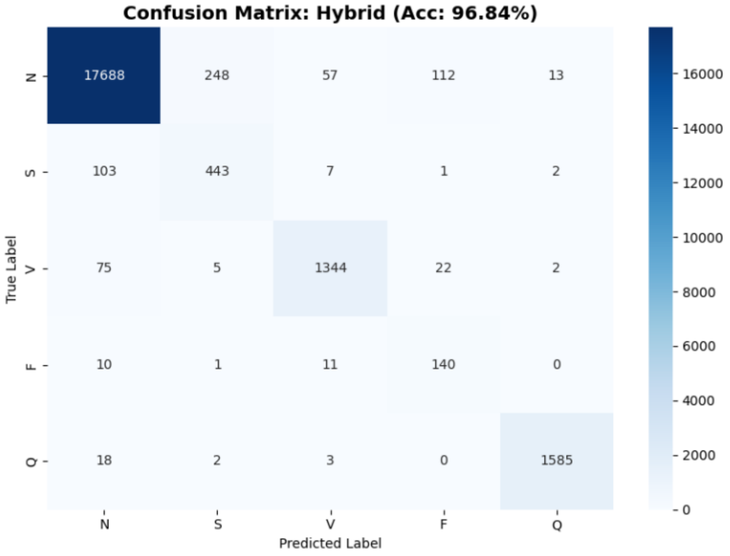

Fig. 3. Confusion Matrix Hybrid Model

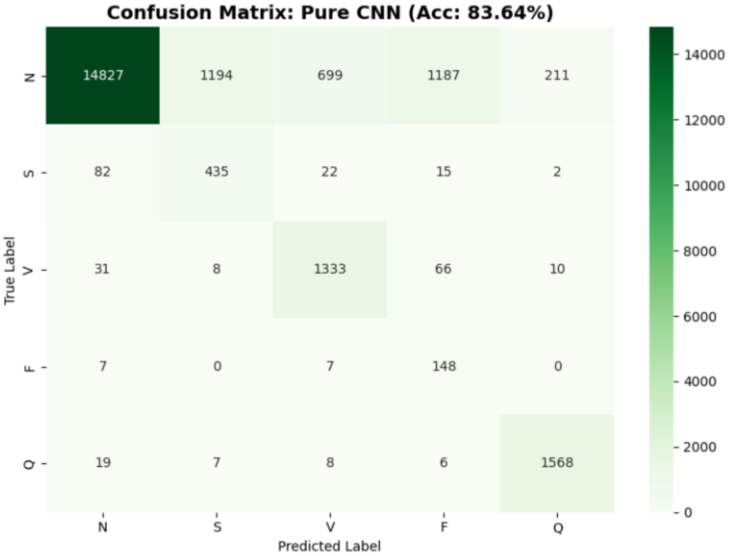

Fig. 4. Confusion Matrix Pure CNN

Furthermore, this improvement directly impacts the model's ability to handle the critical minority classes (S, V, and F). The performance comparison in Fig. 5 highlights this. The Macro Precision (which treats all classes equally) leaped from 0.58 (pure CNN) to 0.81 (hybrid), and the Macro F1-Score increased from 0.63 to 0.85. This proves that the 1D-CNN-SVM model is not only more accurate overall, but it is significantly more balanced, precise, and reliable in identifying the very arrhythmia classes that are often of greatest clinical interest.

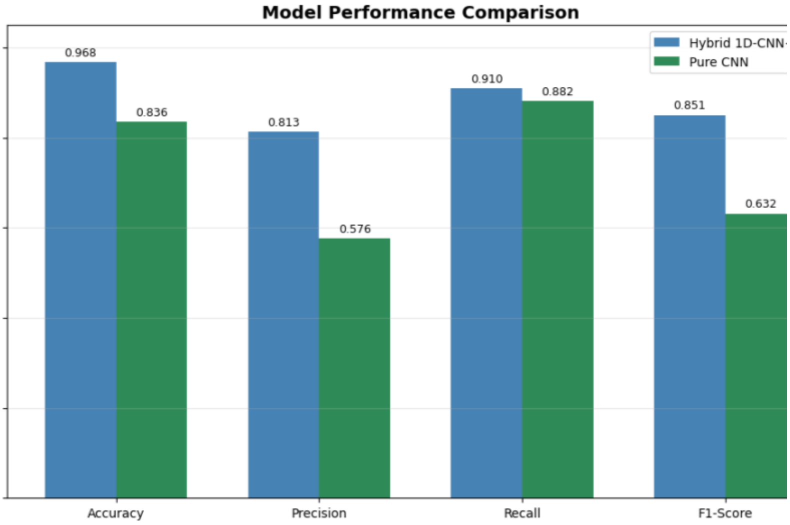

Fig. 5. Comparison of Overall Performance Metrics

The performance comparison in Fig. 5 highlights this. The Macro Precision (which treats all classes equally) leaped from 0.58 (pure CNN) to 0.81 (hybrid), and the Macro F1-Score increased from 0.63 to 0.85. This proves that the 1D-CNN-SVM model is not only more accurate overall, but it is significantly more balanced, precise, and reliable in identifying the very arrhythmia classes that are often of greatest clinical interest. Therefore, the hybrid model is significantly better at balancing the identification of positive cases (*recall*) with the accuracy of positive predictions (*precision*), thereby reducing the number of false positives in classes with fewer samples.

6. Conclusion

This study constructed a hybrid model by combining a 1D-CNN and an SVM for the cardiac arrhythmia classification from ECG signals. According to the experimental result, the proposed hybrid model can achieve an accuracy of 96.84%, which is significantly superior to the 83.64% accuracy achieved by a pure 1D-CNN with a SoftMax. The performance comparison as the Macro Precision rises from 0.58 with the pure CNN to 0.81 with the hybrid model, while the Macro F1-Score improves from 0.63 to 0.85. These gains demonstrate that the 1D-CNN-SVM architecture not only enhances overall accuracy but also delivers a more balanced and reliable classification across all arrhythmia types. As a result, the hybrid model achieves a better equilibrium between capturing true positive cases and ensuring the correctness of positive predictions, effectively reducing false positives in minority classes and improving clinical relevance. Future work could explore optimizing the hyperparameters of both the CNN and SVM, testing the model's robustness on different ECG datasets, and investigating its potential for implementation on low-power wearable devices for real-time monitoring.

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